Ethical Considerations in the use of machine learning for research and statistics

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WS3: Data Ethics

Establishment of a set of **ethical principles** to provide a clear framework to **enable ethical use of Machine Learning** for research and statistics.

Creation of **applied** guidance and/or an accessible tool to **empower statisticians** to apply data ethics principles to their work, so that ethical risks can be identified and mitigated against.

UK Statistics Authority's ethical principles

Public Good	The use of data has clear benefits for users and serves the public good.
Confidentiality, data security	The data subject's identity (whether person or organisation) is protected, information is kept confidential and secure, and the issue of consent is considered appropriately.
Methods and Quality	The risks and limits of new technologies are considered and there is sufficient human oversight so that methods employed are consistent with recognised standards of integrity and quality.
Legal Compliance	Data used and methods employed are consistent with legal requirements such as Data Protection Legislation, the Human Rights Act 1998, the Statistics and Registration Service Act 2007, public equalities duty and the common law duty of confidence.
Public views & engagement	The views of the public are considered in light of the data used and the perceived benefits of the research.
Transparency	The access, use and sharing of data is **transparent**, and is communicated clearly and accessibly to the public.

Review Findings

- There are already a number of **great resources available** to help researchers think about these issues. A handful of these provide applied guidance, as well as high-level principles.
- There is **significant overlap** in the guidance that is already available across the international community.
- The majority of ethical guidance considered as part of this review had a broader **focus on use of AI**, as opposed to a sole focus on ML.
- Clear agreement that **sound and quality methods**, and **transparency** are vital considerations for the use of AI applications in research and statistical production.

Developing our Machine Learning ethics guidance

Identifying user needs

- Scoping review of literature
- Lack of available guidance in this area

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Co-creating guidance

- Engagement with range of stakeholders
- Iterative development with colleagues

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Release of open early draft

- Feedback from wider user community
- Further iterative development
- Review approach & application

Why is ethics important?

Reduce potential harm to all individuals involved in the research

Helps maintain public acceptability around the production of research and statistics

Enables researchers to efficiently access and harness data that supports the production of statistics for the public good.

Promote a culture of ethics by design

The potential for bias

Algorithmic bias

Sample bias

Prejudicial bias

Exclusion bias

CAUTION: Removing sensitive attributes from data to mitigate bias

COMMUNICATING WITH NON-EXPERTS WHEN USING MACHINE LEARNING TECHNIQUES TO ENSURE TRANSPARENCY

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WHAT INFORMATION MIGHT YOUR AUDIENCE FIND HELPFUL?

Take a minute to consider what *you* would like to know about a project if you were approached by someone who wanted to tell you about their machine learning research. Consider this from the perspective of the audience you are trying to communicate with…

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WHAT INFORMATION MIGHT YOUR AUDIENCE NOT FIND HELPFUL?

Take a minute to consider what information you may not find helpful if you were approached by someone who wanted to tell you about their machine learning research from the perspective of the audience you are trying to communicate with…

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MEMBERS OF THE PUBLIC*

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1. What is machine learning?
2. Why did you choose to use machine learning over other methods?
3. What is the aim of the research?
4. Why is the study important, and what will you do with the results?
5. Were there any limitations to your research, or the machine learning methods that you used?
6. How did you access the data and how will it be used?

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1. What will the typical lay person learn from being presented with an algorithm? Are they likely to understand it, or is there a more understandable way of presenting this to a lay audience?
2. Too much information! It may put users off if there is too much information, or if the information presented is hard to read. How can you present the information in a way that is concise and easy to read?

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Accountability

Researchers must be able to justify the method(s) that they have chosen to use. This should be clearly documented.

It is also the collective responsibility of those who develop and train models, and those who deploy pre-existing models to ensure that the use case of a model is clear, and that models are not used beyond their intended use.

Using pre-trained models may be particularly problematic if the model lacks transparency, as it may be harder to identify the processes used to train the model, and existing biases.

Whilst developers cannot stop others from using their models, to remain accountable, **anyone making and training models should try to be explicit in communicating the intended use of a model**, so that models are not created that are then used by others in the wrong way.

Confidentiality

Has data minimisation been appropriately considered? Only the data that is required should be stored and used, and any unnecessary data should be deleted once it has been determined that it is appropriate to do so.

Have you considered whether it is appropriate to anonymise your data, and if so, what the most appropriate method(s) of anonymisation will be?

Have you ensured that your data is being safely stored?

Contact us: **Data.ethics@statistics.gov.uk**

Or visit our website:
https://uksa.statisticsauthority.gov.uk/data-ethics/